Fine Grained Sentiment Classification of Customer Reviews Using Computational Intelligent Technique

C Priyanka [#1], Deepa Gupta [*2]

[#] Department of Computer Science, Amrita School of Engineering,
Amrita Vishwa VidyaPeetham, Bangalore, India
[1] priyadio@gmail.com
[*] Department of Mathematics, Amrita School of Engineering,
Amrita Vishwa VidyaPeetham, Bangalore, India
[2] g_deepa@blr.amrita.edu

Abstract— Online reviews are now popularly used for judging quality of product or service and influence decision making of users while selecting a product or service. Due to innumerous number of customer reviews on the web, it is difficult to summarize them which require a faster opinion mining system to classify the reviews. Many researchers have explored various supervised and unsupervised machine learning techniques for binary classification of reviews. Compared to these techniques, fuzzy logic can provide a straightforward and comparatively faster way to model the fuzziness existing between the sentiment polarities classes due to the ambiguity present in most of the natural languages. But the fuzzy logic techniques are less explored in this domain. Hence in this paper, a fuzzy logic model based on the most popularly known sentiment based lexicon SentiWordNet has been proposed for fine grained classification of the reviews into weak positive, moderate positive, strong positive, weak negative, moderate negative and strong negative classes. Experiments have been conducted on datasets containing reviews of electronic products namely smart phones, LED TV and laptops and have shown to provide fine grained classification accuracy approximately in the range of 74% to 77%.

Keyword- Sentiment analysis, Fine grained Classification, Fuzzy Logic, SentiWordNet, Online reviews

I. INTRODUCTION

The recent expansion of World Wide Web and the social media have dramatically changed the way that people express themselves and interact with others. People can now contribute their opinions and reviews about the products and services they use on the merchant sites and also can interact with others through various blogs, social networking sites and discussion forums. Before Online customer reviews have become an integral and huge source of valuable information for the product manufactures and the service providers to know and analyze the market value of their products which would greatly aid them to formulate strategies for their business and to monitor their reputation in the market. Also, individuals who wanted to purchase the product or use the service would be interested in knowing other's opinion about the product features, pros and cons of the service for decision making. Sentiment Analysis of online reviews has thus become an extremely important area of research today. This visibly emphasizes the motivation behind the need of this research.

Sentiment analysis or opinion mining can be defined as sub discipline of NLP (Natural Language Processing), computational linguistics and text mining that focuses on computational study of opinions, sentiments and emotions expressed in text. It covers a wide range of potential applications which includes e-commerce, politics, movies, tourism, and social networking sites etc. Hence research has been taking place in this domain for so many years. [1] Discusses the main research problems in this area and the techniques adopted so far to solve different levels of sentiment analysis problems.

In our everyday life, we use qualifiers like "good quality", "excellent quality" or "poor quality" to express different degrees of qualification due to the ambiguity rooted in the natural language. In the literature, most of the works concentrate on binary classification of customer reviews rather only very few works have been done for fine grained classification of reviews. Also fuzzy techniques have been less explored. This paper therefore makes an attempt to explore a fuzzy logic model based on the most popularly used lexicon in the field of sentiment analysis, the SentiWordNet for fine granular classification of the reviews into weak positive, moderate positive, strong positive, weak negative, moderate negative and strong negative classes . The remainder of this paper is structured as follows. In Section 2, the existing research works done in the field of sentiment analysis so far has been discussed briefly. In Section 3, the proposed model has been explained in detail. Experiments and results' analysis are tabulated and discussed in Section 4. The conclusion and the future scope for improvement are presented in section 5.

II. RELATED WORK

Research efforts have been done in the field of sentiment analysis since one decade. Researchers have proposed many different techniques for classifying the reviews into positive and negative. Symbolic techniques like semantic orientation approach and supervised or unsupervised machine learning approaches are used to solve the problem of sentiment analysis. Brief description of the work done in this field is described below.

Bo Pang Lee [2] [3], C.Whitelaw [4], Alistair Kennedy [5] and Wen Fan, Shutao Sun and Guohui Song [6] have proposed supervised machine learning approaches with different features sets for binary classification of customer reviews into positive and negative classed. The features extracted include unigrams, bigrams, combination of unigrams and bigrams, adjectival appraisal groups, Bag of words and POS based features. Different machine learning approaches have been applied in each of the works which include Naive Bayes Classifier, Maximum Entropy classifier support vector machines, and multiple classifiers algorithm namely, Bagging and Boosting. Experiments have been performed on various benchmark and home built datasets consisting of reviews on topics like movies, automobiles, travel destinations, news articles and electronic products namely digital cameras, DVD player, kitchen appliances, cellular phone. Accuracy in the range of 81% to 90% has been obtained and most of the previous works have proved to show better results while using SVM classifier. A detailed study has been made in [7] to identify the best combination of features by extracting different features and building the model using support vector machines for binary classification of reviews.

Peter.D.Turney [8] has proposed a simple unsupervised learning algorithm by estimating the semantic orientation of the phrases in the review using Pointwise Mutual Information (PMI) and Information Retrieval (IR) algorithms achieving an average accuracy of 74% .Jaap Kamps [9] has proposed a distance measure to determine the semantic orientation of adjectives using WordNet. Osgood's theory of semantic differentiation, which yields a value between -1 and +1, was applied to measure the semantic orientation of the adjectives. Minqing [10] has proposed a system for feature based summarization of reviews by extracting noun and noun phrases as product features and adjectives as opinion words. Using [11], the semantic orientations of the opinion words were measured and final summary was produced with an accuracy of 84%. Benamara and Farah [12] has proposed three scoring mechanisms for scoring the adverb adjective combination. Tim O'Keefe, Irena Koprinska [13] and Yan Dang [14] proposed sentiment feature based on the SentiWordNet to train SVM Classifier. Feature weighting methods using the SentiWordNet were compared with standard feature weigh ting methods namely frequency, presence and Term Frequency – Inverse Document Frequency (TF-IDF). An accuracy of 87.15% was obtained using Proportional Difference as feature selector and presence as feature weighting mechanism using less than 36% of features when tested on benchmark movie review dataset. Gang Li and Fei Liu [15] introduced clustering based sentiment analysis approach which is a new approach to sentiment analysis. An acceptable and stable clustering results using K- means clustering algorithm has been obtained with less human participation with accuracy in the range 77.17% to 78.33% has been obtained on benchmark movie review dataset.

The machine learning techniques are proposed in the previous works perform binary classification of customer reviews, that is, into positive and negative classes. But due to the ambiguity present in the natural languages, there is a need to perform still fine grained classification of reviews. Also instead of just restricting to classification of reviews, determining the sentiment of individual product characteristics will be very useful for the end customers to take decision before purchasing the product. This can be achieved by implementing fuzzy logic techniques together with natural language processing techniques. Those research works that have been done based on fuzzy logic techniques are briefly discussed.

Guohong Fu and Xin [16] Wang presented a fuzzy set theory based approach to Chinese sentence-level sentiment classification since it provides a straightforward way to model the intrinsic fuzziness between the sentiment polarity classes. Word level, morpheme level and phrase level polarity were determined to calculate the sentence sentiment polarity. Three fuzzy sets were defined to represent three sentiment polarity classes positive, negative and neutral Rise Semi-Trapezoid, Semi-Trapezoid and Drop Semi-Trapezoid membership functions were built to indicate the degree of the opinionated sentence in the different fuzzy sets. By applying principle of maximum membership, final polarity was determined.

Samaneh N Adali, Masrah Azrifah Azmi Murad and Rabiah Abdul Kadir [17] proposed a fuzzy logic model to perform semantic classification of customer reviews into very weak, weak, moderate, very strong, strong subclasses by combinations of adjective, adverb and verb to increase the holistic accuracy of the lexicon approach. Manual scores were assigned for all the words. Triangular membership function was used to model three fuzzy sets namely low, moderate and high. Elton Ballhysa and Ozcan Asilkan [18] proposed a novel approach for discovering the underlying opinion of reviews in Albanian Language by formulating a number of related fuzzy measures and aggregating to yield a resulting score. Relevance measure, Positivity measure, negativity measure and Obscenity measures were calculated using the proposed algorithms. Classification accuracy close to 80% was obtained when experimented on 1000 blog entries. Animesh Khar [19] has proposed a supervised method combining text mining approaches with fuzzy approximation techniques for product ranking by measuring the strength of individual product features. Experiments have been done with reviews on seven different models of digital cameras and a good accuracy has been obtained in predicting product ranking. Wei Wei [20] has also proposed a fuzzy based model to evaluate the quality of Chinese product reviews under the proximity membership principle based on three defined fuzzy sets. Experiments have shown promising performance for this method.

Amit Pimpalkar [21] has proposed a fuzzy based technique for comparative analysis of two products. Sentences from product review are first categorized as subjective and objective using rule based system and dictionary and then the objective sentences are considered for analysis. While analyzing opinion words/phrases are checked with SentiWordnet to obtain semantic score. In fuzzy analysis weights are assigned considering 4 cases e.g. good, very good, not good, not very good etc. (Weight is assigned to (word, its POS tag)). Smileys in reviews are also compared with dictionary and finally the overall score of review is calculated to classify the review. Md. Ansarul Haque [22] implemented a java based application to search tweets from Twitter on any interested field or topic and analyze the sentiment of the same. The application is designed to handle tweets of different languages other than English by using Microsoft translator. The required preprocessing of the tweets is done and finally SentiWordNet is used to determine the score for each word in the tweet. Classification into six different classes namely, Strong Positive, Weak Positive, Positive, Strong Negative, Weak Negative, Negative is done based on total score of the tweet.

Duc Nguyen Trung [23] proposed and implemented a practical system called Tweet Scope based on fuzzy propagation modeling for sentiment analysis of Twitter tweets. Here, twitter data with tweet, re-tweets, user, timestamp etc. are analyzed to find relationship between sentiment words and information propagation in social media. Tweets with similar diffusion pattern are grouped to obtain dependence between information propagation pattern and sentiment words. Mita K. Dalal [24] has proposed an opinion mining system extending feature based classification approach to incorporate the effect of various linguistic hedges. Fuzzy functions have been defined accordingly to emulate the effect of modifiers, concentrators and dilators. Evaluations have been done on dataset containing reviews of four electronic products of different brands.

Based on the study it is evident that the fuzzy logic techniques are less explored in the domain of sentiment analysis. Also, most of the previous works on fuzzy logic have been done by manually assigning scores by human experts which is laborious and time consuming. Also, no understandable model is presented so far which completely make available fuzzy logic techniques in sentiment classification. All the work reported so far have been utilized the partial knowledge of fuzzy theory without reasoning and explanation. This research gap has been attempted and presented in this research work. This is the first attempt of its kind to discuss detailed fuzzy based model in sentiment analysis by combining the standard lexicon to imitate close to human behavior for fine grained classification of reviews. This proposed work has attempted to develop a fuzzy based straightforward model using the scores from a popularly used sentiment based lexicon SentiWordNet for fine grained classification of reviews into weak positive, moderate positive, strong positive, weak negative, moderate negative and strong negative classes.

III. PROPOSED METHODOLOGY

The high level design for the model is given in Fig.1. The working of each block in the high level design is described in subsequent subsections.

A. Preprocessing Based On NLP Techniques

The reviews crawled from the web are unstructured and contains noisy data which has to be preprocessed. Data preprocessing is done to eliminate the incomplete, noisy and inconsistent information and the steps that are followed are listed here. The four preprocessing steps and the three NLP steps performed in this research work are as follows.

- Replacement of words having apostrophe like won’t, can’t, doesn’t etc
- Replacement of repeating characters like Loooooove, soooooo etc.
- Replacement of misspellings like “graet for great”, “desin for design”etc.
- Replacement of short hand words like “hve for have”,”grt for great etc.”
- POS Tagging
- Lemmatization
- Stemming

The preprocessed reviews needs to be POS tagged with appropriate part of speech tags in order to extract opinion information. The POS tagging of the preprocessed sentences is performed using the Stanford POS Tagger 1. A word can take many forms for e.g. the word “perform” can take forms like “performed”, “performing”. It is not possible for all word form to appear in the SentiWordNet. Lemmatization and stemming is performed in case the word in the review is not found in SentiWordNet. Stemming is the process for reducing such inflected words to their stem, base or root form. WordNetLemmatizer is applied for lemmatization and Lanchester stemming algorithm is applied for stemming. The following example shows the raw data and the preprocessed sentence. The text has been carried forward in different steps in the order as specified. The corrected words in the preprocessed sentence have been underlined for clear understanding.

English Sentence: “Excellenttttttt fone !!!!!. Lot of good and useful features, it's very fast and have very good scren of high resolution .loveeeeeee it!“ is transformed into

Preprocessed Sentence: “Excellent phone !!!!!. Lot of good and useful features, it is very fast and have very good screen of high resolution. love it!”.

POS tagged output :“Excellent_JJ phone_NN !!!!!_NNP Lot_NN of_IN good_JJ and_CC useful_JJ features_NNS ._. it_PRP is_VBZ very_RB fast_JJ and_CC have_VBP very_RB good_JJ screen_NN of_IN high_JJ resolution_NN ._. love_NN it_PRP !_.”

B. Extraction Of Opinion Information

Not all the words in the review sentences are providing opinion information about the products or their features. The nouns and noun phrases in the sentences are likely to be the features or product that customers comment on. The opinionated words are mainly adjectives/adverbs that are used to qualify the nouns and express feelings. Two or three consecutive words are extracted from the POS tagged review if their tags conform to any of the patterns given in Table 1. It also shows example opinion phrases for all the specified patterns. For instance, the opinion phrases conforming to pattern 2 (Adverb, Adjective) are “slightly bad” and “extremely worst”. Phrases similar to these examples are extracted from the preprocessed reviews thereby extracting all the opinion information.

TABLE I. Extracted phrase patterns and example opinionated phrases

Pattern No.	Pattern(First Word, Second Word, Third Word)	Opinionated Phrases
1	(Adverb, Adverb, Adjective)	(very very good) (not very good)
2	(Adverb, Adjective)	(slightly bad) (extremely worst)
3	(Adjective)	(good) (excellent) (poor)
4	(Adverb, Adverb, Verb)	(too nicely built) (not poorly performing)
5	(Adverb, Verb)	(perfectly working) (highly recommend)

C. Crisp Inputs from SentiwordNet

The Adjectives, Adverbs, Verbs, which are the linguistic variables for the fuzzy inference system, should be given assigned scores which are the crisp inputs. In SentiWordNet2, each synset of the English lexicon WordNet 3.0 is associated to three numerical scores Obj(s), Pos(s) and Neg(s), describing how objective, positive, and negative the terms contained in the synset are. The process of extracting the score for adjective, adverbs and verbs consists of steps which are depicted in Fig 2.The required word is searched in the SentiWordNet. If the word is not present directly in SentiWordNet, lemmatization and stemming is performed.

In this work, two stemming algorithms are used namely, WordNetLemmatizer3 and Lanchester Stemmer algorithms4 . The output of WordNetLemmatizer is searched in SentiWordNet and if still the word is not found Lanchaster stemming algorithm is applied. The positive words will have high positive score whereas the negative words will have low positive score. Similarly the negative words will have high negative scores and positive words will have low negative scores. Hence it is therefore convenient to measure the positivity and negativity of the word based on positive and negative scores respectively. Therefore, the manipulation can be done by extracting either positive or negative scores since both convey the same information. In case if the word is not found in SentiWordNet even after lemmatization and stemming, it means the word is objective and bears no sentiment. Therefore, a default value of 0 is assigned for both positive score and negative score of the word. In this work, after finding out the word in SentiWordNet, the positive scores of all the senses corresponding to the word are extracted. The maximum value of this list is chosen as the final score for the word. The scores of SentiWordNet range from 0 to 1, which is very low, due to which interpretation from the membership function plot becomes difficult. Hence the final score of the word is multiplied by 10 for scaling purpose and assigned as the crisp input for the input linguistic variables. The crisp input for the word is the scaled value of the positive score of the word directly extracted from SentiWordNet which may ot be sufficient enough for fine grained classification. This crisp input should therefore be converted into fuzzy sets by applying suitable membership functions which are explained in detail in the following respective sections.Figures and Tables

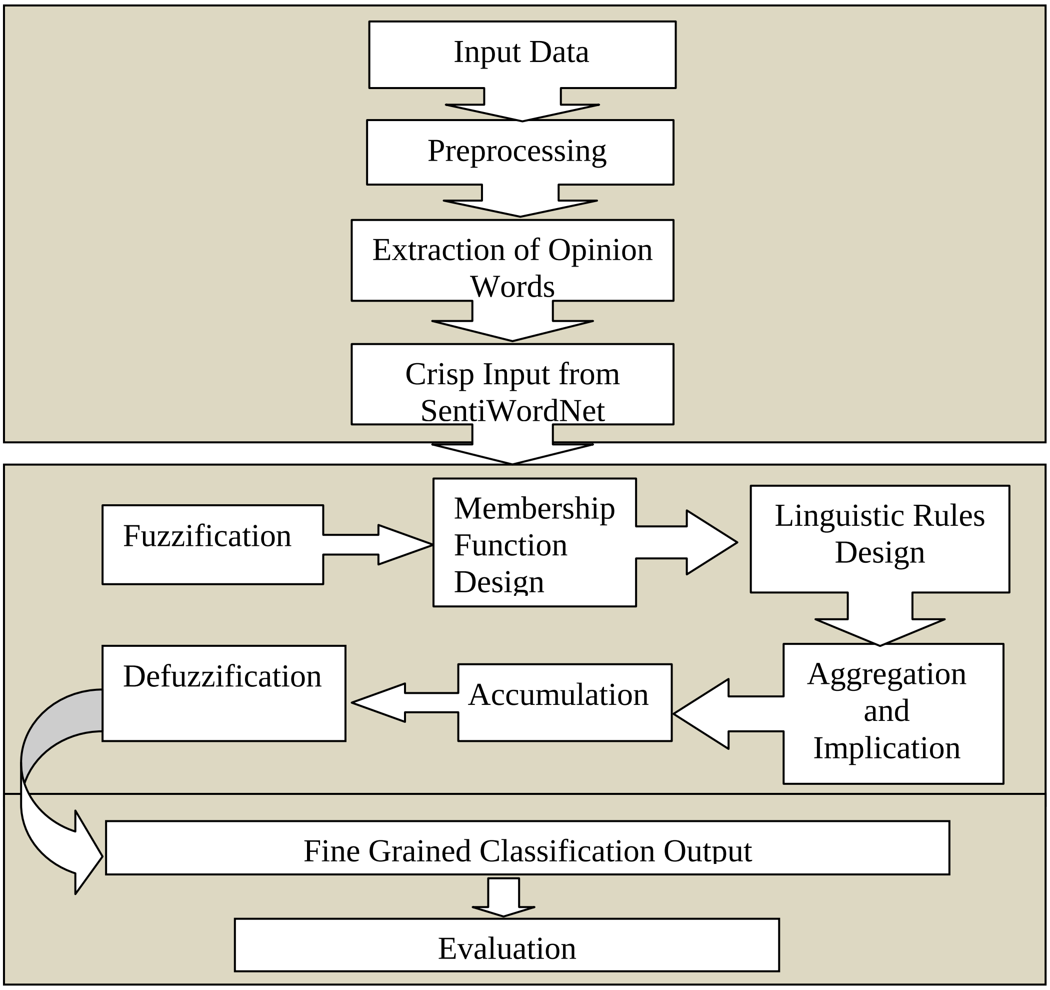

Fig. 1. Schematic Diagram of the proposed methodology

D. Fuzzification

In a fuzzy system, the first step includes the identification of input and output linguistic variables. Since sentiment information is provided mostly by adjectives, verbs and the intensity of the sentiment is conveyed by the adverbs, in this work “Adjective”, “Adverb” and “Verb” are taken as input linguistic variable. The aim of the proposed fuzzy model is to classify the reviews into polarity classes, for e.g. Weak Positive, Moderate Positive etc. Hence, the “Degree of Polarity” is taken as the output linguistic variable. The input and the output variables for the system are of REAL data type, that is, they accept real values.

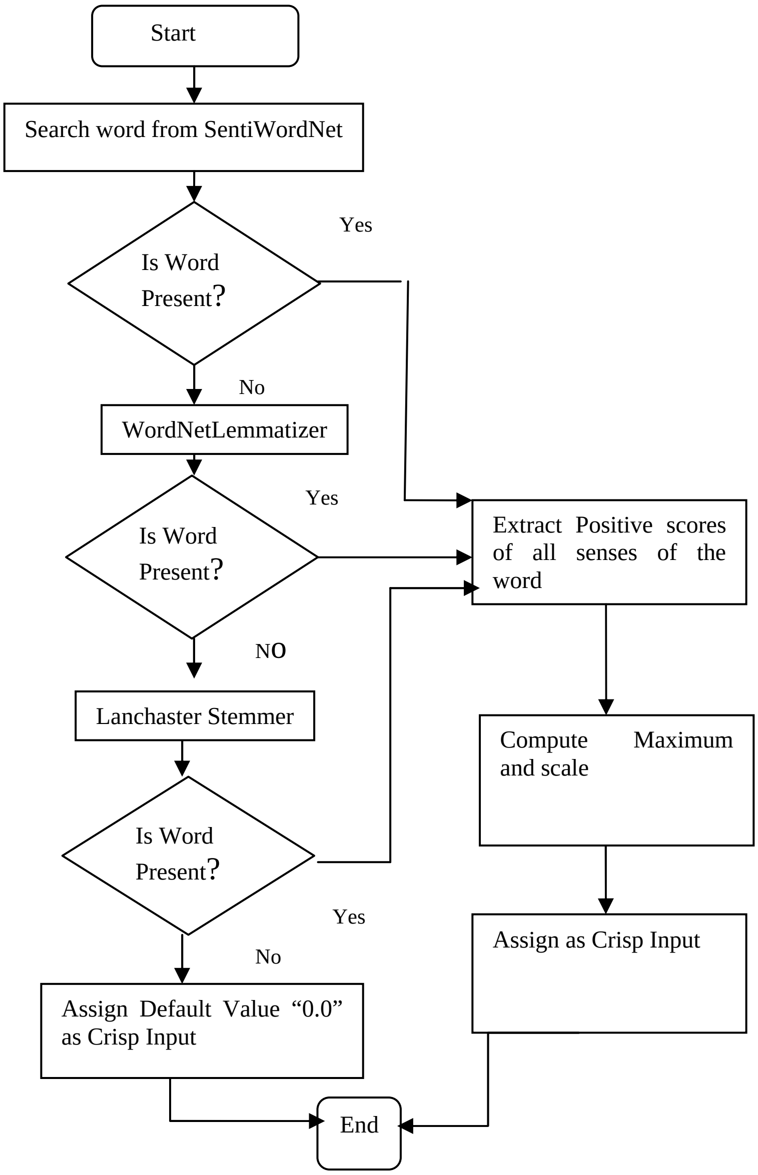

Fig. 2. Extraction of Crisp Input from SentiWordNet

It is generally easier and better for us to imagine the fuzzy sets of the input and output variables as linguistic terms instead of numbering the fuzzy sets, therefore, fuzzy sets are named accordingly. The first main stage in a fuzzy system is fuzzy partition and fuzzification, where linguistic variables are divided into suitable fuzzy sets by partitioning of each variable. In other words, fuzzification is the partitioning of each variable into fuzzy sets (linguistic terms) as well as applying a membership function over each fuzzy set (partition). The fuzzy sets defined for the input and output linguistic variables for this work are shown in Table 2. All the fuzzy sets are given respective notations in braces and in all the rules the respective notations are used. There are 6 fuzzy sets defined for Adjective and Verb because in most cases the opinion is conveyed by the adjectives and verbs only. Therefore partitioning them into many classes will be easier for final classification of the reviews into six classes as discussed. Since only the strength of the opinion is conveyed by adverbs, it is enough to define only three fuzzy sets for adverbs. Thus based on these two input linguistic variables, the output fuzzy set is determined which conveys the degree of polarity of the review.

TABLE III. Linguistic Variables and Fuzzy Sets

Input	
Linguistic Variable	**Fuzzy Sets**
Adjective	High Negative (HN), Moderate Negative(MN), Low Negative (LN), Low Positive (LP) , Moderate Positive (MP), High Positive (HP)
Verb	
Adverb	Low (L), Moderate (M) , High (H)
Output	
Linguistic Variable	**Fuzzy Sets**
Degree of Polarity	Strong Negative (SN), Moderate Negative (MN), Weak Negative (WN), Weak Positive (WP), Moderate Positive (MP), Strong Positive (SP)

E. Membership Function Design

The Crisp Values of the Linguistic Variables are converted to the given fuzzy sets by the function known as Membership Function [27]. The inputs are mapped into the degree of membership by proper membership functions for the partitions of linguistic variables as linguistic term sets or linguistic values. There are several forms of membership functions. Generally, the shapes of membership functions are triangular, trapezoidal, bell-like, or Gaussian forms that might be drawn linearly or non-linearly. The crisp quantities, as support, are on the horizontal axis. The results of the membership function μ(x) are projected on the vertical axis (y). The quantity on the horizontal axis is the" base variable" and represents the universe of discourse; while the quantity on the vertical axis is the membership degree to the fuzzy set. The selection of suitable membership functions for fuzzy sets is one of the important part in a fuzzy system which perfectly represents the fuzzy modeling. In this work, Triangular, Semi- Trapezoidal and Piece-wise Linear Membership Functions are used for respective fuzzy terms by carefully analyzing the scores of the lexicon provided in SentiWordNet.

Fig.3 shows the elected fuzzy sets and the corresponding membership function, defined by translating the variable "Adjective" into six linguistic terms {"High Negative", "Moderate Negative" , "Low Negative" , "Low Positive" , "Moderate Positive", "High Positive" }: as they shift towards the left the positivity increases. Conversely, a shift towards the right indicates the increase in negativity.

For instance, the triangular membership function is chosen for the fuzzy set 'Moderate Positive'. It is defined with end points as (4.5, 0) and (7, 0) and high point as (6, 1) in (1). In a similar fashion, Semi Trapezoidal membership function is chosen for the fuzzy set "High Positive" and shown in (2). In the same manner, membership functions are defined for the other fuzzy sets by selecting appropriate end points and are depicted in the plot shown in Fig 3.

$$\mu_{MP}(x) = \begin{Bmatrix} 0 & if\ x \le 4.5 \\ \frac{x-4.5}{1.5} & if\ 4.5 \le x \le 6 \\ \frac{7-x}{1} & if\ 6 \le x \le 7 \\ 0 & if\ x \ge 7 \end{Bmatrix} \tag{1}$$

The Semi Trapezoidal function "High Positive" with end point (6.8, 0) and (9, 1) is defined by

$$\mu_{HP}(x,a,b) = \begin{Bmatrix} 0, & if\ x < 6.8 \\ (x-6.8)/2.2, & if\ 6.8 \le x \le 9 \\ 1, & if\ x > 9 \end{Bmatrix} \tag{2}$$

Similar to the input linguistic variable “Adjective”, six fuzzy sets are formed for “Verb namely {“High Negative”, “Moderate Negative”, “Low Negative”, “Low Positive”, “Moderate Positive”, “High Positive”} and suitable membership functions are defined for all the fuzzy sets by analyzing the scores from SentiWordNet . For instance, the triangular membership function is chosen for the fuzzy set ‘Low Positive’. It is defined with end points as (1.25, 0) and (3, 0) and high point as (2, 1) in (3). In a similar fashion, semi Trapezoidal membership function is chosen for the fuzzy set “High Positive” and shown in (4). In the same manner, membership functions are defined for the other fuzzy sets by selecting appropriate end points and are depicted in the plot shown in Fig 4.

$$\mu_{LP}(x) = \begin{Bmatrix} 0 & if \;\; x \le 1.25 \\ \dfrac{x-1.25}{0.75} & if \;\; 1.25 \le x \le 2 \\ \dfrac{3-x}{1} & if \;\; 2 \le x \le 3 \\ 0 & if \;\; x \ge 3 \end{Bmatrix} \tag{3}$$

The Semi Trapezoidal function “High Positive” with end point (4.5, 0) and (7, 1) is defined by

$$\mu_{HP}(x,a,b) = \begin{Bmatrix} 0, & if \; x < 4.5 \\ (x-4.5)/2.5, & if \; 4.5 \le x \le 7 \\ 1, & if \; x > 7 \end{Bmatrix} \tag{4}$$

FUZZY SET	MEMBERSHIP FUNCTION
High Negative	Piece-wise Linear
Moderate Negative	Triangular
Low Negative	Triangular
Low Positive	Triangular
Moderate Positive	Triangular
High Positive	Semi - Trapezoidal

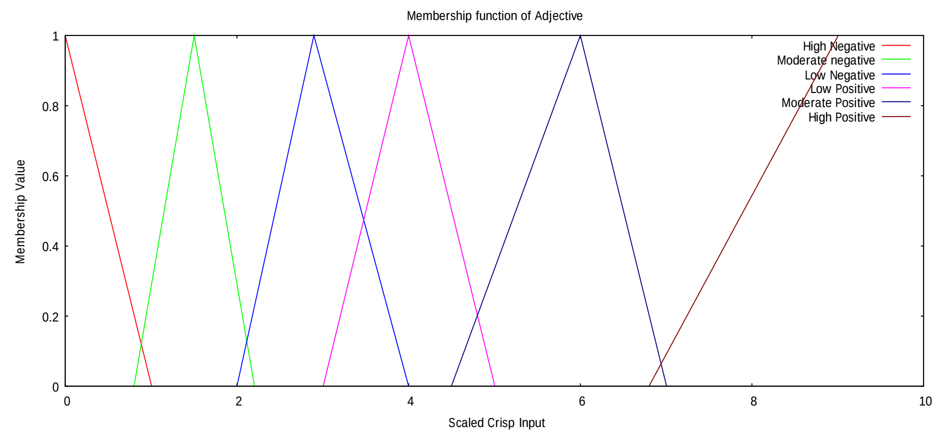

Fig. 3. Membership Function for Adjective with Six Linguistic Terms

The intensity enforced on adjectives by adverbs ranges from low to high. The three fuzzy sets low, moderate and high and their corresponding membership functions are shown in Fig 5. The Triangular and Semi-trapezoidal function are defined for the three "Adverb" fuzzy sets with their respective end points similar to the one defined in (1) and (2).

F. *Linguistic Rules Design*

Rule Block is the signal part of a fuzzy inference system that contains rules, defined by the empirical knowledge of experts and the knowledge learnt from data. In other words, the prepared fuzzy sets in the previous step are used in rules-making, which are either by expert rule or by data-based rule. The rule block includes fuzzy operators to combine all fuzzy sets of linguistic variables per rule as well as rule accumulation. Simple operators are applied such as OR (maximum) or AND (minimum). The result of this step is used determine the degree of polarity of the customer reviews. The general form of the fuzzy rule can be expressed as: If   x1 is ADV AND/OR x2 is ADV AND/OR x3 is ADJ/VERB THEN x4 is DEG where, ADJ/VERB is a set containing the fuzzy sets of the input linguistic variable "Adjective" and "Verb". ADV is a set containing the fuzzy sets of the input linguistic variable "Adverb". DEG is a set containing the fuzzy sets of the output linguistic variable "Degree of polarity". x1, x2, x3 represent the fuzzy variables which are the opinion words of the opinion phrases extracted from the customer reviews.. x4 represents the fuzzy variable "Degree of Polarity". The ADJ/VERB, ADV and DGE sets are discussed in Table II. The minimum operator "AND" is used between the antecedent variables in the rules defined in our fuzzy inference system. Table 3 shows sample rules of the IF – THEN rules designed for the developed fuzzy inference system to determine the degree of polarity of the customer reviews.

FUZZY SET	MEMBERSHIP FUNCTION
High Negative	Piece-wise Linear
Moderate Negative	Triangular
Low Negative	Triangular
Low Positive	Triangular
Moderate Positive	Triangular

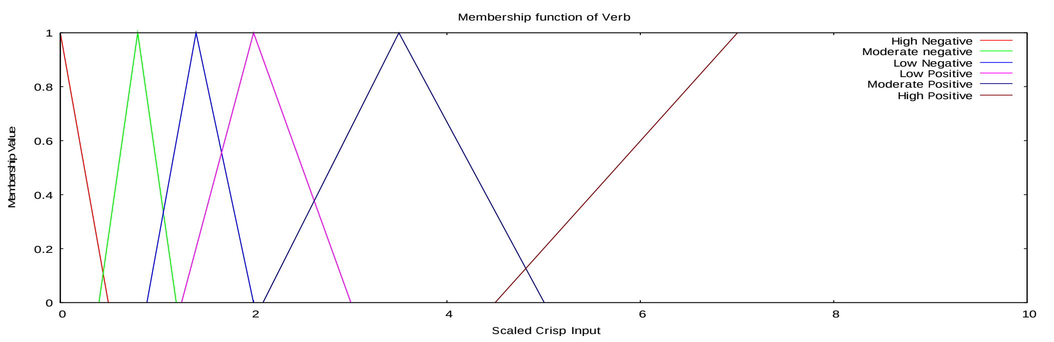

Fig. 4. Membership Function for Verb with six Linguistic Terms

FUZZY SET	MEMBERSHIP FUNCTION
Low	Piece-wise Linear
Moderate	Triangular
High	Semi - Trapezoidal

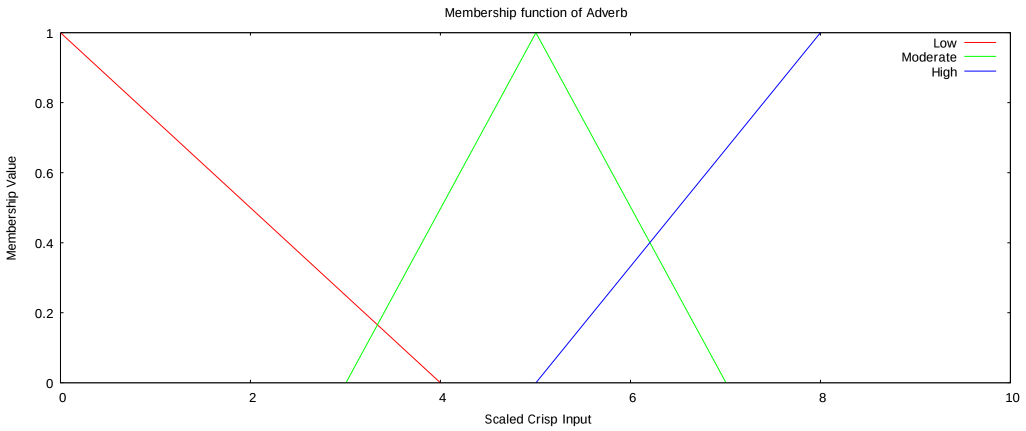

Fig. 5. Membership Function for Adverb with Three Linguistic Terms

TABLE IIIII. Sample If – then Rules

S.No	Rules
1	IF (adverb1 IS L) AND (adverb2 IS L) AND (adjective IS LN) THEN (degree IS SN);
2	IF (adverb1 IS L) AND (adverb2 IS L) AND (adjective IS MN) THEN (degree IS WN);
3	IF (adverb1 IS L) AND (adverb2 IS L) AND (adjective IS HN) THEN (degree IS moderate_neg);
4	IF (adverb1 IS L) AND (adverb2 IS L) AND (adjective IS LP) THEN (degree IS WP);
5	IF (adverb1 IS L) AND (adverb2 IS L) AND (adjective IS MP) THEN (degree IS WP);
6	IF (adverb1 IS L) AND (adverb2 IS L) AND (adjective IS HP) THEN (degree IS MP);
7	IF (adverb1 IS L) AND (adverb2 IS M) AND (adjective IS LN) THEN (degree IS SN);
8	IF (adverb1 IS L) AND (adverb2 IS M) AND (adjective IS MN) THEN (degree IS MN);
9	IF (adverb1 IS L) AND (adverb2 IS M) AND (adjective IS HN) THEN (degree IS MN);
10	IF (adverb1 IS L) AND (adverb2 IS M) AND (adjective IS LP) THEN (degree IS WP);
11	IF (adverb1 IS L) AND (adverb2 IS M) AND (adjective IS MP) THEN (degree IS WP);
12	IF (adverb1 IS H) AND (adverb2 IS L) AND (adjective IS LN) THEN (degree IS MN);
13	IF (adverb1 IS H) AND (adverb2 IS L) AND (adjective IS HN) THEN (degree IS SN);
14	IF (adverb1 IS H) AND (adverb2 IS M) AND (adjective IS LN) THEN (degree IS MN);

IF_THEN rules that can support all possibilities are in total of about 324. In this work, rules that are irrelevant are pruned out and a total of 78 rules have been defined. Consider for example the IF THEN rule from Table III, IF (adverb1 IS L) AND (adverb2 IS L) AND (adjective IS LN) THEN (degree IS SN).

Here, if the adverb1 belongs to the fuzzy set “Low”, adverb2 belongs to the fuzzy set “Low” and adjective belongs to the fuzzy set “Low Negative”, then degree of polarity of the corresponding opinion phrase belongs to the fuzzy set “Strong Negative”. Similarly other rules are also interpreted in the similar way and are fired one after the other.

G. Aggregation and Implication

The first step is to take the crisp inputs of the input linguistic variables "Adjective" and "Adverb" and determine the degree to which they belong to each of the appropriate fuzzy sets through their respective membership functions. The input is always a crisp numerical value (in this case the interval between 0 and 10) and the output is a fuzzy degree of membership in the qualifying linguistic set (always between 0 and 1).

After the inputs are fuzzified, the degree to which each part of the antecedent is satisfied for each rule is known. In this work, 3 types of rules have been defined: antecedent with one part, two parts and three parts. The logical fuzzy operator "AND" is applied to the antecedent of the rules having more than one part in order to obtain one single number that represents the result of the antecedent for that rule. The fuzzy "AND" operator simply selects the minimum of the values. This is the process of aggregation. Now after aggregating, implication process is implemented for each rule. The implication process reshapes the consequent of the rule using the single number given by the aggregation of the antecedent, and the output is a fuzzy set. The implication method used here is same as the "AND" method: minimum, which truncates the output fuzzy set which is the Degree of polarity of the POS pattern.

H. Accumulation

Decisions are based on the testing of all the rules and hence the rules must be combined in some order to make a decision. Accumulation is a process by which the outputs of each rule are combined into a single fuzzy set. The input of the accumulation process is the list of truncated output functions returned by the implication process for each rule. The output of the accumulation process is one fuzzy set for the output variable "Degree of polarity". The accumulation process is commutative and hence the order of the rules is unimportant. The Maximum accumulation method is used in this work.

I. Defuzzification and Output

The next stage is to map the fuzzy values into crisp values to determine a final score for the extracted POS pattern. In this stage, the Centre of Gravity (CoG) defuzzification operator is used which returns the centre of area under the curve and is given in " Eqn (5) ". The accumulated fuzzy rules outputs are converted to a single crisp value which represents the degree of polarity for each of the POS based pattern extracted. For the output linguistic variable Degree of Polarity, five fuzzy terms are defined and all are represented by triangular membership functions as shown in the plot given in Fig.6. The Centre of gravity defuzzification is defined in Eqn (6) as

$$z^{*} = \int \frac{\mu_c(z).zdz}{\mu_c(z)dz} \tag{5}$$

Where, z* is the defuzzified value and μC (z) is the accumulated output of the list of output functions returned by the application of implication process for each rule.

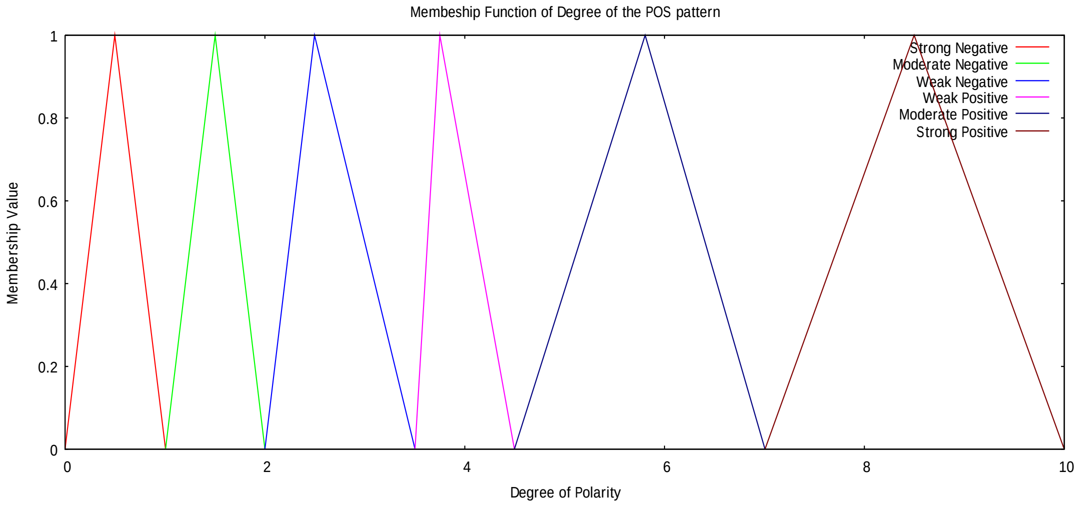

Fig.6. Membership Function for Output with Six Linguistic Terms

For instance, the triangular membership function for the fuzzy set 'Strong Positive' is defined in (6). The function is defined with end points as (7, 0) and (10, 0) and high point as (8, 1). In a similar fashion, triangular membership functions are defined for the other fuzzy sets by selecting appropriate end points and high point.

$$\mu_{SP}(x) = \begin{cases} 0 & if\ x \le 7 \\ \frac{x-7}{1} & if\ 7 \le x \le 8 \\ \frac{10-x}{2} & if\ 8 \le x \le 10 \\ 0 & if\ x \ge 10 \end{cases} \tag{6}$$

J. Fine Grained Classification Output

The described fuzzy logic based model is used to determine a crisp score based on the fuzzy sets defined for the input linguistic variables for each of the POS based pattern that is extracted. Now to determine the degree of polarity of the entire customer review is, the average of all the scores provided for each of the POS pattern extracted from the review is calculated which is shown in Eqn (7).

$$\text{Fine Grained Score} = \frac{\sum_{i=1}^{n} D_i}{N} \tag{7}$$

Where, Di is defuzzified output of the ith extracted pattern and N is the total number of POS patterns extracted from a review. The fine grained score ranges from 0 to 10. The degree of polarity can be identified from the score with the help of the plot shown in fig 5. As we move towards right in the graph indicates positivity and as we move towards left indicates negativity. The range for each degree of polarity is pre-defined and hence the class to which the customer review belongs to can be determined from this final fine grained score.In this stage, the Centre of Gravity (CoG) defuzzification operator is used which returns the centre of area under the curve and is given in " Eqn (5) ". The accumulated fuzzy rules outputs are converted to a single.

IV. DATA STATISTICS AND RESULT ANALYSIS

The experiments performed to prove the advantage of the proposed fuzzy based model has been discussed.. The Stanford Part of Speech tagger developed by Stanford University has been used to tag the reviews. The PyFuzzy-0.1.05, a python based fuzzy logic module has been used for implementation of the proposed model in which the required coding is done in Python 2.7 programming language. The results and analysis have been furnished in order to demonstrate the usefulness of the proposed model.

A. Corpus Statistics

Experiments have been conducted on three datasets containing reviews of electronic products namely smart phones, laptops, and LED TV. The reviews have been collected from the web6 and annotated by us manually based on the star rating provided in the website. The reviews that are rated 1-2 are considered as negative and 4-5 are considered as positive. The star rating information has not been used anywhere in the proposed fuzzy model but this information helps us to calculate the binary classification accuracy of our proposed model. The detailed statistics of the three data corpus is presented in Table 3. The reviews have been chosen in such a way that average word count per review ranges from 42 to 82 approximately. This proposed model has been therefore tested on reviews irrespective of the nature of the review in terms of its length. The total number of reviews in each dataset ranges from 800 to 1000 approximately. Therefore, the experimental results obtained reveal that the proposed fuzzy based model can be applicable to any dataset containing electronic products' reviews irrespective of the dataset size as well as the review length.

TABLE III. Corpus Statistics

Review Dataset	# of reviews	Avg word count per review	Avg sentence count per review
Domain : Smart Phones			
Positive Review	538	42.69	2.95
Negative Review	580	49.52	2.91
Domain : Laptops			
Positive Review	585	67.50	3.78
Negative Review	592	81.94	4.02
Domain : LED TV			
Positive Review	580	70.34	3.05
Negative Review	510	75.19	4.39

B. Experimental Results and Analysis

In order to evaluate the efficiency and usefulness of the proposed model, the model has been tested on many opinion phrases of different degrees of polarity extracted from the customer reviews of the corpus given in Table 3. The defuzzified output of some of the opinion phrases has been tabulated in Table 4. There is significant difference between the scores of the phrase "Bad" and "Good" which is 2.689 and 5.766 respectively. Similarly in the phrases "Very Good" and "Very Excellent" , the adverb "Very" has been used to intensify the positive polarity of the words "Excellent" and "Good". Hence scores are also relatively high compared to the other phrases which is 8.3333. It is also clear from Table 4 that the system is able to show significant difference between the opinion phrases containing verb. The scores of the phrases " Not Working" and "Badly Working" are 1.5 which are relatively low compared to the score of the opinion phrase "Working" which is 5.068. This clearly shows that the two former phrases are negative compared to the latter one. Similarly the model provides for the phrases "Nicely Working" and "Excellently Working" a higher score of 6.772 and 8.389 respectively thereby proving the positive polarity of these phrases. Thus the scores provided by the proposed model for the opinion phrases given in the Table 4 clearly confirms that the proposed fuzzy model is able to capture the intrinsic fuzziness between the polarity classes using the scores from the lexicon SentiWordNet.

The average of all the defuzzified output scores of the opinion phrases extracted from a customer review has been used to calculate a final output score for the review as per the Eqn(7). This score determines the final class to which the review belongs to. To classify the reviews into positve and negative classes based on this score, cut off value which partitions the entire set into two classes has to be fixed. Experiments have been performed with different cut off values and the accuracy in (%) for binary classification of reviews into positive and negative classes for those different cut off values has been determined and plotted in Fig 7. Binary classification accuracy ranges from 74% to 77% as shown in fig 7 . It is evident from the graph that better classification accuracy can be obtained with the cut off value of 3.2. Similar experiments have been performed in order to determine the cut off values for all the six classes of fine grained classification. Based on the results of those experiments, the range for each class is computed and tabulated in Table VI. The results of the fine grained classification for all the three datasets have been tabulated in Table 7. The accuracy of fine grained classification ranges from 74% to 76%.

TABLE IV. Results of sample opinion phrases

Opinion Phrases	Defuzzified Output	Opinion Phrases	Defuzzified Output
Not bad	3.9166	Not Very Good	5.766
Very bad	1.5	Very Worst	1.5
Bad	2.689	Fantastic	5.7574
Slightly Bad	3.9567	Very Excellent	8.333
Not Good	2.6666	Excellent	5.766
Very Good	8.333	Not Working	1.5
Good	5.766	Badly Working	1.5
Slightly Good	3.484	Nicely Working	6.772
Worst	2.689	Excellently Working	8.389
Slightly Worst	3.9567	Working	5.068
Very Very bad	0.5		

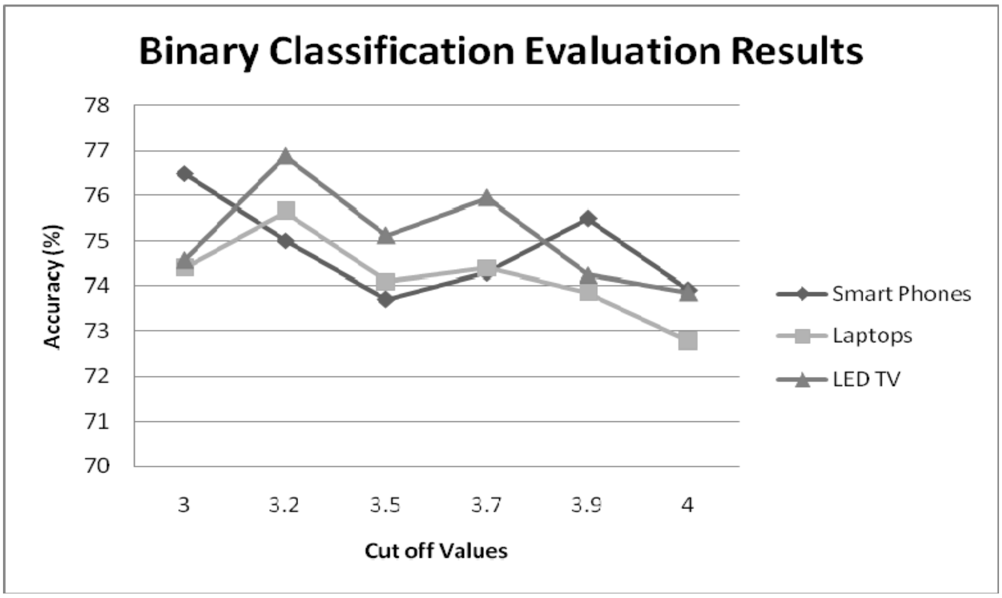

Fig.7. Accuracy in (%) for different cut off values for the three datasets

The experiments thus performed is sufficient to evaluate the efficiency and advantage of the proposed fuzzy based model. The results tabulated in Table 4, Table 5 and Table 6 have been analyzed and the findings have been listed below.

It can be seen from the Table 4 that the defuzzified output values of the phrases “Slightly Good” is 3.484, “Not Good” is 2.666, “Good” is 5.766 and“Very Good” is 8.333. It is clearly evident from these values that the scores has been assigned for the phrases by the model according to its degree of polarity. The phrase “ Slightly Good” has a score little higher than the phrase “Not Good” and the Phrase “Good” has a score little higher than the other two “Slightly Good” and “Not Good”. The phrase “Very Good” has a score higher than all the other three phrases. Logically, the sentimental meaning of the phrases and the assigned scores are hand in hand with each other.

TABLE V. Range for the six classes

Class	**Range**
Strong Negative	(0 – 1)
Moderate Negative	(1 – 2)
Weak Negative	(2 – 3.5)
Weak Positive	(3.5 – 4.5)
Moderate Positive	(4.5 – 7)
Strong Positive	(7 – 10)

TABLE VI. Evaluation results for fine grained classification

Domain	**Accuracy (%)**
Smart phones	76.5%
Laptops	75%
LED TV	74.3%

- It is also evident from Table 4 that the scores that have been assigned by the proposed model for the opinion phrases containing verb are according to their degree of polarity. The defuzzified output value for the phrases " Not Working" and "Badly Working" are very less which implies that they bear negative sentiment. Similarly the output value for the phrases " Nicely Working" and "Excellently Working" are higher which implies that they bear posituve sentiment. Also there is significant difference between the scores of the phrases "Nicely Working" and "Excellently Working" which clearly indicates the degree to which each of the phrases are positive.
- Experiments have been performed with numerous opinion phrases in order to know the real advantage of directly using the scores of the lexicon SentiWordNet for proposed fuzzy based model. It is found that the scores provided in SentiWordNet for most of the adjectives can be used directly and only scores for few adjectives require revision.
- The defuzzified output values for some of the opinion phrases containing verb show less satisfactory results. Analysis of these output values reveals that the scores provided by SentiWordNet for a quiet larger number of verbs are not that suited for direct usage in our proposed fuzzy model. Revision of these scores either manually or through automatic approaches may be required to obtain more satisfactory results which will also lead to significant improvement of the final classification accuracy results.
- The accuracy in (%) ranges from 74% to 77% for binary classification of reviews into positive and negative classes as given in Fig.7 Comparing the accuracy (%) with respect to the different cut off values for all the three datasets, it is evident that fixing the cut off value to 3.2 would give better binary classification accuracy.

V. Conclusion and Future Scope

In this paper, we have proposed a fuzzy logic based sentiment analysis model for fine grained classification of customer reviews into weak positive, moderate positive, strong positive, weak negative, moderate negative and strong negative classes. The model has been designed in such way that the scores from the popularly known sentiment based lexicon, SentiWordNet has been effectively used insteal of manual scoring which is tedious and laborious task. Experimental results have shown to produce an accuracy in the range of of 72% to 75% when tested on three datasets containing reviews of electronic gadgets. Though the accuracy produced by the proposed fuzzy based model is not that comparable to the accuracy produced by the supervised machine learning approaches discussed in section 2, this model do not require any kind of labelled data which is expensive with lot of prior human effort. It is also computationally less intensive and less time consuming. Also, instead of restricting to only classification of reviews, determining the sentiment of each product characteristics from the reviews will be very useful which can be achieved by extending the proposed fuzzy based model by combining with natural language processing techniques.

In future work, word sense disambiguition of the opinion word can be performed before extracting its sentiment score from SentiWordNet to improve the performance of the model.Few revisions in the scores of SentiWordNet , either manually or through automated approaches by analyzing data from different datasets, can also lead to significant improvement in the final results. Modifying the membership functions of the defined fuzzy sets also have scope for enhancement of the final accuracy results.

REFERENCES

[1] Roney Feldman, “Techniques and Applications for Sentiment Analysis”, Communications of the ACM, Vol. 56 No. 4, Pages 82-89,2013

[2] Bo Pang and Lillian Lee, Shivakumar Vaithyanathan, "Thumbs up? Sentiment Classification using Machine Learning Techniques." In the Proceedings of the Conference on Empirical Methods in Natural Language Processing (EMNLP)”, Philadelphia, Association for Computational Linguistics, Volume 10 Pages 79-86, July 2002.

[3] Bo Pang and Lillian Lee "A Sentimental Education: Sentiment Analysis Using Subjectivity Summarization Based on Minimum Cuts.", Proceeding ACL '04 -Proceedings of the 42nd Annual Meeting on Association for Computational Linguistics, pp. 271-278, 2004

[4] C. Whitelaw, N. Garg, and S. Argamon, "Using Appraisal Groups for Sentiment Analysis," in Proceedings of the 14th ACM International Conference of Information and Knowledge Management(CIKM),Pages 625-631,2005.

[5] Alistair Kennedy and Diana Inkpen," Sentiment Classification of Movie Reviews Using Contextual Valence Shifters ", Journal: Computational Intelligence, vol. 22, vol. 22, no. 2, pp. 110-125, 2006.

[6] Wen Fan, Shutao Sun,Guohui Song ,"Sentiment Classification for Chinese Netnews Comments Based on Multiple Classifiers Integration, "Fourth International Joint Conference on Computational Sciences and Optimization , Pages 829 -834 , April 2011.

[7] C. Priyanka and Deepa Gupta, “Identifying the best feature combination for sentiment analysis of customer reviews” , International Conference on Advances in Computing, Communications and Informatics, ICACCI 2013, Pages 102-108, Mysore, India, August 22-25, 2013.

[8] Peter D. Turney, “Thumbs Up or Thumbs Down? Semantic Orientation Applied to Unsupervised Classification of Reviews”, Proceedings of the 40th Annual Meeting of the Association for Computational Linguistics (ACL), Philadelphia, pp. 417-424, july 2002

[9] Jaap Kamps, Maarten Marx, Robert J. Mokken, Maarten de Rijke, “Using WordNet to Measure Semantic Orientations of Adjectives”, in Proceedings of LREC-04, 4th International Conference on Language Resources and Evaluation, Volume IV, page 1115 – 1118, 2004

[10] Minqing Hu and Bing Liu ,"Mining and Summarizing Customer Reviews", in Proceedings of the tenth International Conference on Knowledge discovery and data mining (KDD’04), Pages 168-177, Seattle, Washington, USA, August 22–25, 2004.

[11] Andrea Esuli and Fabrizio Sebastiani, "Sentiwordnet: A Publicly Available Lexical Resource for Opinion Mining," in Proceedings of the 5th Conference on Language Resources and Evaluation , LREC’06, page 417-422, 2006.

[12] Benamara, Farah, Cesarano, Carmine, Picariello, Antonio,Reforgiato, Diego & Subrahmanian, V.S, "Sentiment Analysis: Adjectives and Adverbs are Better than Adjectives Alone " in Proceedings of the International Conference on Weblogs and Social Media (ICWSM), Short paper, 2007.

[13] Tim O’Keefe ,Irena Koprinska, “Feature Selection and Weighting Methods in Sentiment Analysis, in Proceedings of 14th Australasian Document Computing Symposium, Sydney, Australia, December 2009.

[14] Yan Dang, Yulei Zhang, and Hsinchun Chen, "A Lexicon-Enhanced Method for Sentiment Classification: An Experiment on Online Product Reviews," Journal IEEE Intelligent Systems, Volume 25 Issue 4, Pages 46-53, July 2010.

[15] Gang Li, Fei Liu, "A Clustering-based Approach on Sentiment Analysis," in International Conference on Intelligent Systems and Knowledge Engineering (ISKE), Pages 13 – 16, November 2010.

[16] Guohong Fu and Xin Wang, “Chinese Sentence-Level Sentiment Classification Based on Fuzzy Sets,” COLING '10 Proceedings of the 23rd International Conference on Computational Linguistics: Posters Pages 312-319, 2010.

[17] Samaneh N adali, Masrah Azrifah Azmi Murad and Rabiah Abdul Kadir , “Sentiment Classification of Customer Reviews Based on Fuzzy logic ,” in International Symposium on Information Technology (ITSim), Vol 2 Pages 1037-1044, 2010.

[18] Elton Ballhysa and Ozcan Asilkan,“A fuzzy approach for blog opinion mining–an application to Albanian lanuage”, in AWER Procedia Information and technology & computer science, Vol I Pages 1143 - 1150, 2011.

[19] Animesh Kar and Deba Prasad Mandal , “Finding Opinion Strength Using Fuzzy Logic on Web Reviews,” International Journal of Engineering and Industries, volume 2, Number 1, March, 2011

[20] Wei Wei, Yang Xiang, Qian Chen, Xin Guo, “Evaluating Quality of Chinese Product Reviews Based on Fuzzy Logic,” Emerging Research in Web Information Systems and Mining Communications in Computer and Information Science , Volume 238, Pages 328-333,2011

[21] Amit Pimpalkar, Tejashree Wandhe, M. Swati Rao, Minal Kene, “Review of Online Product using Rule Based and Fuzzy Logic with Smiley’s” , IJCAT - International Journal of Computing and TechnologyVolume 1, Issue 1, February 2014.

[22] Md. Ansarul Haque, Tamjid Rahman , “Sentiment Analysis by using Fuzzy Logic” , International Journal of Computer Science, Engineering and Information Technology (IJCSEIT), Vol. 4,No. 1, February 2014.

[23] Duc Nguyen Trung and Jason J. Jung, “Sentiment Analysis Based on Fuzzy Propagation in Online Social Networks: Case study on TweetScope?” Computer Science and Information Systems 11, Pages 215 -228,

[24] Mita K. Dalal and Mukesh A. Zaveri, “Opinion Mining from Online User Reviews Using Fuzzy Linguistic Hedges”, Applied Computational Intelligence and Soft Computing, Hindawi Publishing Corporation, Volume 2014, Published 20 February 2014.

[25] Fuzzy Logic with Engineering Applications, 2nd Edition by Timothy J. Ross , ISBN: 978-0-470-86074- 8,650 pages, June 2004.

[26] J. Breckling, Ed., The Analysis of Directional Time Series: Applications to Wind Speed and Direction, ser. Lecture Notes in Statistics. Berlin, Germany: Springer, 1989, vol. 61.

[27] S. Zhang, C. Zhu, J. K. O. Sin, and P. K. T. Mok, “A novel ultrathin elevated channel low-temperature poly-Si TFT,” IEEE Electron Device Lett., vol. 20, pp. 569–571, Nov. 1999.

[28] M. Wegmuller, J. P. von der Weid, P. Oberson, and N. Gisin, “High resolution fiber distributed measurements with coherent OFDR,” in Proc. ECOC’00, 2000, paper 11.3.4, p. 109.

[29] R. E. Sorace, V. S. Reinhardt, and S. A. Vaughn, “High-speed digital-to-RF converter,” U.S. Patent 5 668 842, Sep. 16, 1997.

[30] (2007) The IEEE website. [Online]. Available: http://www.ieee.org/

[31] M. Shell. (2007) IEEEtran webpage on CTAN. [Online]. Available: http://www.ctan.org/tex-archive/macros/latex/contrib/IEEEtran/

[32] FLEXChip Signal Processor (MC68175/D), Motorola, 1996.

[33] “PDCA12-70 data sheet,” Opto Speed SA, Mezzovico, Switzerland.

[34] A. Karnik, “Performance of TCP congestion control with rate feedback: TCP/ABR and rate adaptive TCP/IP,” M. Eng. thesis, Indian Institute of Science, Bangalore, India, Jan. 1999.

[35] J. Padhye, V. Firoiu, and D. Towsley, “A stochastic model of TCP Reno congestion avoidance and control,” Univ. of Massachusetts, Amherst, MA, CMPSCI Tech. Rep. 99-02, 1999.

[36] Wireless LAN Medium Access Control (MAC) and Physical Layer (PHY) Specification, IEEE Std. 802.11, 1997.